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RESEARCH ARTICLE

Do We Fully Understand the Critical Success Factors of Customer Satisfaction with Industrial Goods? - Extending Festge and Schwaiger's Model to Account for Unobserved Heterogeneity

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Abstract: This paper extends Festge and Schwaiger's (2007) model of customer satisfaction with industrial goods by accounting for unobserved heterogeneity. The application of a novel response-based segmentation approach in partial least squares path modeling (PLS-PM) - the finite mixture partial least squares (FIMIX-PLS) methodology - opens the way for the effective identification of distinctive customer segments. In comparison to previous studies in this field, group-specific path model estimates reveal each customer segment's particular characteristics as well as other differentiated findings. Hence, this contribution demonstrates that structural equation modeling studies on the aggregate data level can be seriously misleading and makes a strong case for segment-specific customer satisfaction analyses.

Keywords: Customer satisfaction · Structural equation model · PLS path modeling · Segmentation · Finite mixture · Latent class · Unobserved heterogeneity

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Introduction

Given its importance and established relation with customer retention and corporate profitability, customer satisfaction is fundamental for businesses' long-term success (e.g., Anderson et al. 2004). In addition, this finding applies to capital-intensive goods in business-to-business relationships within industrial markets (Bingham and Raffield 1990). Effective customer management requires a clear-cut understanding of the relevant success factors of customer satisfaction in order to identify marketing activities that can positively contribute to the business's overall success (e.g., Höck and Ringle 2009). However, do we fully understand the critical success factors of customer satisfaction with industrial goods?

Customer satisfaction has attracted considerable research during the past decades (e.g., Fornell et al. 1996; Hackl and Westlund 2000; Höck et al. 2009). Nevertheless, relatively little attention has been paid to industrial markets. Early studies on the business-to-business sector (e.g., Tanner 1996; Qualls and Rosa 1995) only reflected specific aspects of customer satisfaction instead of conceptualizing this construct by using multi-item scales (Backhaus and Bauer 2000). With regard to industrial markets, Homburg and Rudolph (2001) developed the first notable measuring concept for customer satisfaction. Their INDSAT scale consists of seven distinct satisfaction dimensions, each of which exerts a significant influence on customers' overall satisfaction. However, owing to the scale's methodological problems, which relate to its reflective construct specification, Festge and Schwaiger (2007) proposed a new approach to measuring customer satisfaction.

Reverting to Rossiter's (2002) C-OAR-SE procedure for the establishment of scales to measure marketing constructs, Festge and Schwaiger (2007) developed a questionnaire consisting of 52 items with which to measure 15 constructs. Using data collected from 12 countries, the authors carried out a partial least squares path modeling (PLS-PM) analysis (e.g., Henseler et al. 2009; Lohmöller 1989; Wold 1974) to identify potential drivers of customer satisfaction in this market. The results of the study reveal that only two of these critical success drivers (satisfaction with quotations and satisfaction with machines and systems) have a significant impact on customer satisfaction. Hence, marketers have a limited radius of activities with which to increase customer satisfaction.

This result is highly surprising considering that in the study's scale development process, both suppliers and customers have identified many more potential success factors as being critical for customer satisfaction. Although Festge and Schwaiger (2007) rule out potential methodological issues (e.g., correlations between the constructs, nonlinear relationships) by carrying out supplementary analyses, the authors believe that the lack of significant effects is related to the restrictive assumption that the data originate from a single homogeneous population (i.e., that the global model used fully represents all observations). However, if the population were heterogeneous, but treated as homogeneous, the results would be seriously distorted (e.g., Muthén 1989; Ringle et al. 2009a).

Literature often acknowledges that there are no truly homogeneous consumer segments (e.g., Wedel and Kamakura 2000). Moreover, studies report substantial consumer heterogeneity within a given product or service class (Wu and DeSarbo 2005). For example, in the field of customer satisfaction research, Jedidi et al. (1997) developed a model-based segmentation approach in structural equation modeling to uncover several customer segments that differ considerably in terms of the importance they attach to satisfaction's various dimensions. Similarly, Hahn et al. (2002) reveal significant heterogeneity in a PLS-PM analysis of customers' perceived satisfaction with and loyalty to convenience stores as well as their perception of these stores quality. These studies' results show that the identification of customer segments regarding inner model estimates is a fundamental problem in respect of forming decisive interpretations when working with structural equation models (SEMs). However, the heterogeneity problem is rarely addressed – neither in a covariance-based, nor in a variance-based framework. This may lead to inappropriate PLS-PM results and, therefore, to flawed conclusions as demonstrated by Ringle et al. (2009a).

This research proposes an extension of Festge and Schwaiger's (2007) model by accounting for unobserved heterogeneity. A novel response-based segmentation approach – finite mixture partial least squares (FIMIX-PLS) – allows data classification based on the heterogeneity of the inner path model estimates (Ringle et al. 2005a). By applying this new approach, we extend the original modeling framework by introducing a categorical moderator variable, whose modalities represent different segments within the data, whereas the strength of the relationships between the latent variables varies across the segments (Bauer and Curran 2004). This paper's primary objective is to revisit Festge and Schwaiger's (2007) model in order to provide a differentiated and more complete picture of customer satisfactions' antecedents in the industrial goods market, which is of great importance for management decisions. Likewise, this study underlines the analytic potentials of FIMIX-PLS as a means to evaluate PLS-PM results on an aggregate data level.

The remainder of this paper is organized as follows: The next section provides a brief overview of approaches to deal with heterogeneity in PLS-PM. Subsequently, the FIMIX-PLS methodology and a systematic approach to apply FIMIX-PLS are presented. Thereafter, Festge and Schwaiger's (2007) original model is introduced, followed by the analysis and discussion of the FIMIX-PLS results. The paper concludes with managerial and methodological implications, a discussion of this study's limitations, and directions for future research.

Uncovering Heterogeneity and Data Segmentation in PLS Path Modeling

Traditionally, heterogeneity in SEMs is accounted for by postulating homogenous segments based on prior knowledge. Alternatively, conventional clustering techniques may be applied on the manifest data level. However, observable characteristics, such as demographic variables, often gloss over heterogeneity (Wedel and Kamakura 2000), while sequential clustering strategies such as k-means do not provide satisfactory outcomes in terms of uncovering heterogeneity in inner PLS path model estimates (Ringle 2006; Sarstedt and Ringle 2010). In fact, since heterogeneity is frequently unobservable and its source is usually unknown, observations cannot easily be classified into subpopulations.

Different latent class approaches have been proposed to response-based clustering in a PLS-PM framework. These procedures generalize decision tree (Sánchez and Aluja 2006), PLS typological regression (Esposito Vinzi et al. 2008), fuzzy regression (Palumbo et al. 2008), and genetic algorithm (Ringle and Schlittgen 2007; Ringle et al. 2009b) approaches to PLS-PM. Developments in this line of research differ substantially in terms of the types of heterogeneity dealt with, distributional assumptions, and the interpretability of the resulting segments. According to a review by Sarstedt (2008a), the key approach to segmenting data in a PLS-PM framework is FIMIX-PLS, as it exhibits several beneficial statistical properties compared to competing approaches. FIMIX-PLS was first introduced by Hahn et al. (2002) and later fostered by Ringle et al. (2005a, 2009a). It combines the PLS-PM method's strengths with the advantages of classifying market segments according to finite mixture models.

In a finite mixture model-based approach to clustering, it is assumed that the data stem from a source with several subpopulations (Frühwirth-Schnatter 2006). Each subpopulation is modeled separately and the overall population is a mixture of these subpopulations. That is, each data point $\boldsymbol{x}_i$, $i=1,\ldots,n$, is understood as a realization of the mixture density with S ($S<\infty$) segments, where

$$f_{i|s}(\mathbf{x}_i|\boldsymbol{\theta}_s) = \sum_{s=1}^{S} \rho_s \; f_{i|s}(\mathbf{x}_i), \tag{1}$$

with $\rho_s > 0 \; \forall s, \; \Sigma_{s=1}^{S} \rho_s = 1$, $f_{i|s}(\cdot)$ being a density function and $\boldsymbol{\theta}_s$ depicting the segment-specific vector of unknown parameters of segment s. The set of mixing proportions ρ determines the relative mixing of the S segments in the mixture. Based on segment membership's fitted posterior probabilities, it is possible to cluster the data into S classes (McLachlan and Peel 2000). Finite mixture modeling enables researchers to estimate parameters and to, simultaneously, partition observations into S segments with a similar response structure, thus avoiding well-known biases that occur when segments are analyzed separately (Fraley and Raftery 2002).

The FIMIX-PLS Algorithm

Based on the finite mixture concept, FIMIX-PLS simultaneously estimates the model parameters and ascertains the data structure's heterogeneity within a PLS-PM framework. The initial FIMIX-PLS step is to estimate a path model by using the PLS-PM algorithm on manifest variables in the outer measurement models. The resulting latent variable scores in the inner path model are then employed to run the second step of the FIMIX-PLS algorithm. The path models' segment-specific heterogeneity is concentrated in the estimated relationships between the latent variables. FIMIX-PLS captures this heterogeneity and calculates the probabilities of segment membership in respect of each observation so that the data fit into a predetermined number of segments S. Assuming that each endogenous latent variable η_i is distributed as a finite mixture of conditional multivariate normal densities $f_{i|s}(\cdot)$, the segment-specific distributional function is defined as follows:

$$\boldsymbol{\eta}_i \sim \sum_{s=1}^{S} \rho_s \; f_{i|s}\left(\boldsymbol{\eta}_i | \boldsymbol{\xi}_i, B_s, \boldsymbol{\Gamma}_s, \boldsymbol{\Psi}_s\right), \tag{2}$$

where ξ_i is an exogenous variable vector in the inner model in respect of observation i, B_s is the path coefficient matrix of the endogenous variables, and Γ_s is the path coefficient matrix of the exogenous latent variables; Ψ_s depicts the matrix of each segment's regression variances of the inner model on the diagonal, zero else. The mixing proportion ρ_s determines the relative size of segment s (s=1,…,S) with $\rho_s>0$ $\forall s$ and $\Sigma_{s=1}^{S}\ \rho_s = 1$. Substituting $f_{i|s}(\eta_i, |\xi_i, B_s, \Gamma_s, \Psi_s)$ results in:[1]

$$\boldsymbol{\eta}_i = \sum_{s=1}^{S} \rho_s \left[\frac{1}{(2\pi)^{J/2}\sqrt{|\boldsymbol{\Psi}_s|}}\right] \exp\left\{-\frac{1}{2}\left((I - \mathrm{B}_s)\boldsymbol{\eta}_i + (-\boldsymbol{\Gamma}_s)\boldsymbol{\xi}_i\right)' \boldsymbol{\Psi}_s^{-1}\left((I - \mathrm{B}_s)\boldsymbol{\eta}_i + (-\boldsymbol{\Gamma}_s)\boldsymbol{\xi}_i\right)\right\}, \tag{3}$$

where J depicts the number of endogenous latent variables in the inner model. Given this parametric model and i.i.d. data, the estimation of the model parameters can proceed via the maximum likelihood method, in which the complete log-likelihood function lnlc can be written as:

$$\mathrm{Ln}L_C = \sum_{\mathrm{i}=1}^{\mathrm{N}} \sum_{\mathrm{s}=1}^{\mathrm{S}} \mathrm{z_{is}} \ln(f(\eta_i \mid \xi_i, \mathrm{B}_s, \Gamma_s, \Psi_s)) + \sum_{i=1}^{N} \sum_{s=1}^{S} \mathrm{z_{is}} \ln(\rho_s), \tag{4}$$

where z_{is} is a 0/1 assignment variable of observation i to segment s.

Parameter estimation is carried out by using a modified version of the EM algorithm, which allows for the simultaneous, yet independent, estimation of the segment-specific regression functions. Consequently, the EM algorithm's maximization step calculates S independent maximum likelihood estimators by utilizing the ordinary least squares technique (Hahn et al. 2002). The segment size ρ_s as well as the parameter matrices ξ_i, B_s, and Γ_s and Ψ_s of the conditional probability function are stated as results of the M-step, while the provisional estimates of P_{is} are computed according to Bayes's (1763/1958) theorem:

$$P_{is} = \frac{\rho_s f_{i|s}(\eta_i|\xi_i, B_s, \Gamma_s, \Psi_s)}{\sum_{s=1}^{S} \rho_s f_{i|s}(\eta_i|\xi_i, B_s, \Gamma_s, \Psi_s)} \forall i, s. \tag{5}$$

By differentiating between dependent (i.e., endogenous latent) and explanatory (i.e., exogenous latent) variables inside the structural model, the approach follows a mixture regression concept (Wedel and Kamakura 2000).

FIMIX-PLS has been successfully applied in different contexts (e.g., Ringle et al. 2009a, 2009c; Sarstedt et al. 2008) and has performed favorably in simulation studies (e.g., Esposito Vinzi et al. 2007; Ringle et al. 2005a). However, there are several thorny issues related to the approach. First, to carry out parameter estimation, FIMIX-PLS relies on the EM algorithm, which may converge to local optima and not the true (global) maximum of the likelihood function. However, to determine whether this has occurred, the researcher can repeat the procedure, starting with different (random) values. If the results of the repeated estimation nets different parameter estimates, the result with the highest likelihood should be chosen (McCutcheon 2002). Second, for model identification purposes, the algorithm imposes a distributional assumption on the endogenous latent variables. Even though this assumption runs contrary to the PLS-PM approach's non-parametric character (Sarstedt 2008a), simulation studies show that FIMIX-PLS is robust despite distributional misspecification (Esposito Vinzi et al. 2007). Furthermore, Tenenhaus et al. (2009) show that the endogenous latent variables approach a normal distribution, even if both the manifest and exogenous latent variable scores are far from normal. Lastly, to ensure the algorithm's convergence, the endogenous and exogenous latent variables' measurement models are kept constant across all iterations. Consequently, FIMIX-PLS only captures heterogeneity in the inner model relationships. However, measurement models can be updated by partitioning the data along the lines of explanatory variables, which eventually leads to the same classes as those identified by FIMIX-PLS, thus resulting in segment-specific parameter estimates.

To fully exploit the approach's capabilities, Ringle et al. 2009a) propose a systematic approach to FIMIX-PLS clustering (Fig. 1) which serves as a guideline for the following analyses. In FIMIX-PLS Step 1, the basic PLS-PM algorithm provides path modeling results by using the aggregate dataset. Step 2 uses the resulting latent variable scores in the inner path model to run the FIMIX-PLS algorithm as described above. The most important computational results of this step are the probabilities P_{is}, the mixing proportions ρ_s, the class-specific estimates B_s and Γ_s for the path model's inner relationships, and Ψ_s for the (unexplained) regression variances.

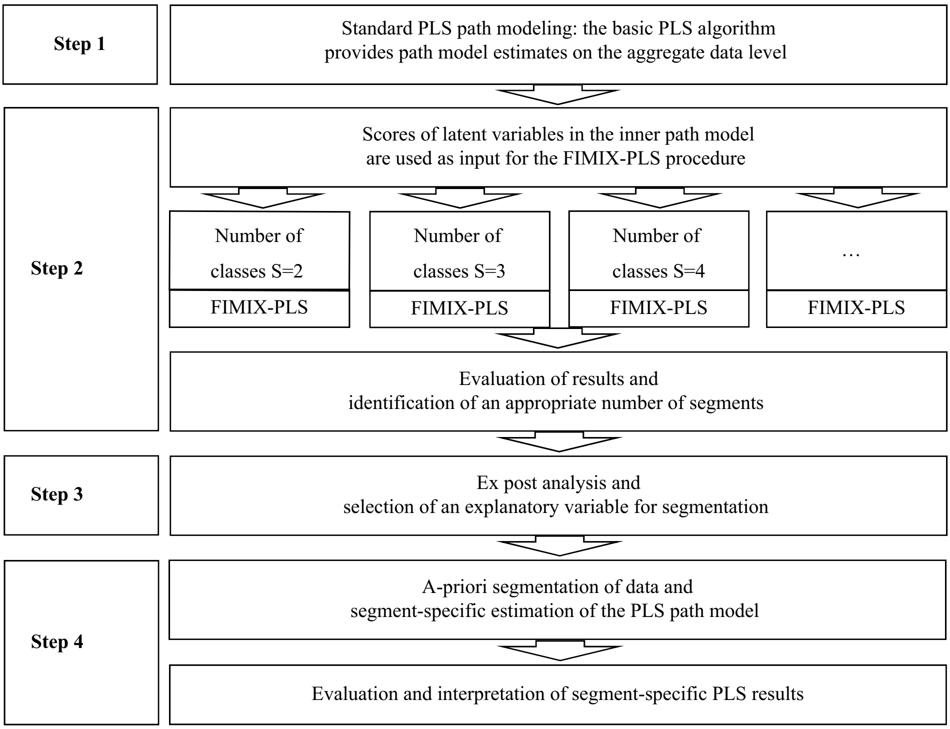

Fig. 1: Systematic Application of FIMIX-PLS

The methodology fits each observation with the finite mixture's probabilities P_{is} into each of the predetermined number of classes. However, on the basis of the FIMIX-PLS results, one has to determine whether the approach detects and treats heterogeneity in the inner PLS path model estimates by means of (unobservable) discrete moderating factors. The task of Step 2 is to explore this objective by analyzing the results of different numbers of S classes. In determining the number of classes that should be retained from the data, researchers frequently revert to a heuristic approach by, for example, building on information or classification criteria. In the past, a vast number of different criteria were developed to assess the number of segments. All these criteria have different theoretical underpinnings and statistical properties, and their performance has been evaluated in several simulation studies in different contexts (e.g., Andrews and Currim 2003; Sarstedt 2008b).

In situations where FIMIX-PLS results indicate that heterogeneity in the overall dataset can be reduced through segmentation by using the best fitting number of S classes, an explanatory variable must be uncovered in the ex post analysis (Step 3). In this step, data are classified by means of an explanatory variable, which serves as a new input for segment-specific computations in the PLS-PM approach (Step 4). An explanatory variable should not only include similar clustering of data, as indicated by the FIMIX-PLS results, but also allow for the distinct clusters' interpretability (Sarstedt and Ringle 2010). The evaluation and interpretation of the segment-specific PLS-PM outcomes that result from the explanatory variable require a PLS multi-group analysis (e.g., Henseler 2007). Hence, this analysis in Step 4 permits determining significant differences not only in the inner path model but also in the formative measurement models. Thereby, the identification of an exploratory variable in the ex post analysis allows to precisely interpret the different segments and to circumvent the limitation of FIMIX-PLS to only focus on the inner PLS path model relationships.

Model and Data

Festge and Schwaiger (2007) investigated the epistemic nature of customer satisfaction and its driver constructs in order to develop a formative measure of customer satisfaction with industrial goods. Based on a thorough literature review as well as interviews with experts, the authors develop a set of 52 performance items, which are then merged to form 15 anteceding driver constructs in respect of overall satisfaction. In line with Bergkvist and Rossiter's (2007) argumentation, Festge and Schwaiger (2007) operationalize the construct customer satisfaction with a (reflective) single item.[2]

The PLS path model analysis draws on a leading manufacturer of custom-made machinery and systems' customer responses. In 2006, data were collected in 12 countries by means of a standardized mail questionnaire. The dataset includes $n=281$ fully completed questionnaires. All the respondents rated their satisfaction with one or more suppliers of the respective company by means of indicators for each driver construct. All variables are measured on seven-point scales with higher scores denoting higher levels of satisfaction.

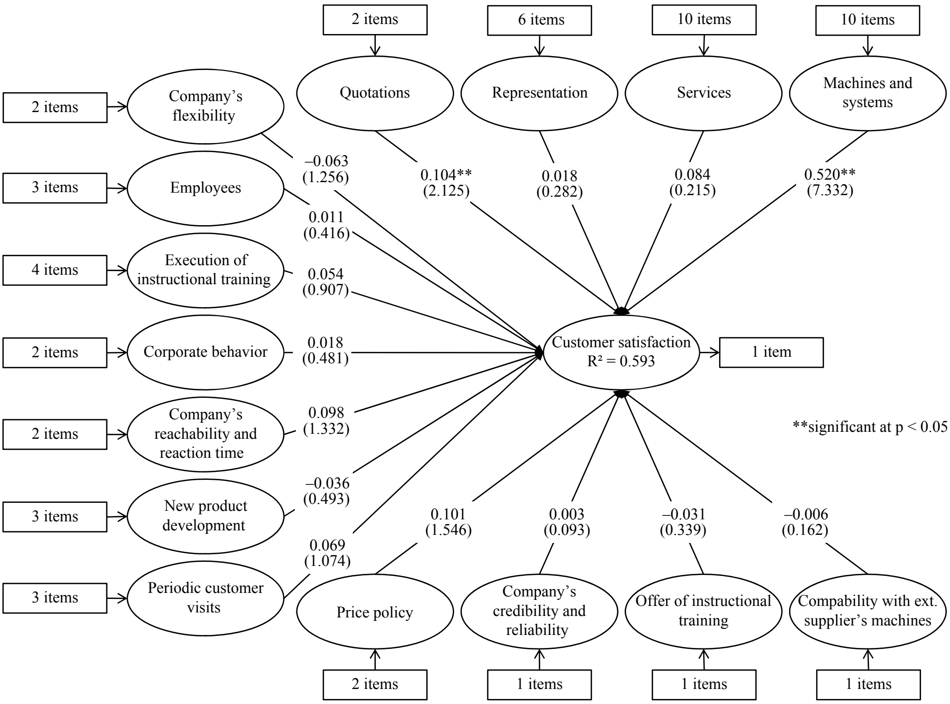

Fig. 2: Festge and Schwaiger's (2007) Model of Customer Satisfaction

Figure 2 illustrates the research model with PLS-PM estimates from the original study. The R-square value (0.593) of the endogenous construct "customer satisfaction" is fully acceptable in terms of the aggregate-level analysis. The global model results clearly indicate that merely two success drivers ("satisfaction with the machines and systems" and "satisfaction with the quotations") have a significant influence on customer satisfaction with industrial goods.

As Festge and Schwaiger (2007) pointed out, this result is surprising if one considers that the identified performance features are relevant from both the supplier's and customer's point of view. Moreover, Homburg and Rudolph (2001) established that all of the constructs identified during their scale development process significantly influence customers' overall satisfaction.

We believe that unobserved heterogeneity significantly affects the inner path model relationships in Festge and Schwaiger's (2007) study. In fact, past customer satisfaction studies provide strong evidence that structural equation modeling results may be substantially distorted if unobserved heterogeneity is not handled properly (e.g., Hahn et al. 2002; Jedidi et al. 1997). The use of FIMIX-PLS allows this kind of heterogeneity to be uncovered by determining appropriate regression model mixtures. This may increase model fit considerably and offer further differentiated conclusions that lead to more effective strategies.

Analysis and Results

By using the SmartPLS software (Ringle et al. 2005b), FIMIX-PLS is applied to the data with ten replications (Step 2 in Fig. 1). Initially, FIMIX-PLS results are computed in respect of two segments. Thereafter, the number of segments is successively increased. In addition, commonly applied information criteria, in the context of mixture regression models, are computed for each solution (Sarstedt 2008b). These criteria include Akaike's information criterion (AIC), the consistent AIC (CAIC), or the Bayes information criterion (BIC). Table 1 provides information criteria values for a varying number of segments.

A comparison of the segment-specific information criteria reveals that the minimum value has been achieved in respect of a two-segment solution for BIC and CAIC. Moreover, Sarstedt et al. (2009) suggest that CAIC works well with FIMIX-PLS. In a six-segment solution, as indicated by AIC, the smallest segment exhibits a FIMIX-PLS segment size of 8%, which contradicts meaningful a-priori segmentation. Furthermore, AIC is known to overestimate the number of suitable segments in finite mixture models (e.g., Andrews and Currim 2003; Sarstedt et al. 2009). In addition, a two-segment solution is supported by the distribution of segment membership's (P_{is}) posterior probabilities. More than 75% of all observations are assigned to one of the two segments with $P_{is} \geq 0.7$. The normed entropy criterion (EN; Ramaswamy et al. 1993) value of 0.513 reflects this outcome. This value is relatively high compared to the EN of 0.430 arrived at by Hahn et al. (2002) in their primary FIMIX-PLS application. This kind of result indicates that the two segments differ sufficiently and, thus, allow a comprehensible interpretation of the results. Lastly, the FIMIX-PLS probabilities of membership P_{is} are used for a-priori clustering and segment-specific PLS-PM analyses, respectively. Each observation is assigned to one of the two segments in accordance with its highest membership probability. The two datasets are separately (group-wise) used as input matrices for the manifest variables in order to estimate PLS path models for each group of observations.

Within the scope of structural equation modeling, model assessment requires researchers to assess the reliability and validity of the measures used. Chin (1998) proposed a catalogue of non-parametric criteria for assessing partial model structures. A systematic application of these criteria requires a two-step process: The assessment of the structural model's properties are only worthwhile if the formative measurement model exhibits a satisfactory degree of validity (Henseler et al. 2009).

Evaluation of the formative measurement model: The outer weights can be interpreted as the indicators' relative importance in respect of forming the summated scale that represents the latent variable. Some indicators help explain the latent variable with small to high outer weights, while other indicators' impact does not differ significantly from

Table 1: Model Selection Statistics

	s=2	**s=3**	**s=4**	**s=5**	**s=6**
lnL	−365.174	−387.348	−300.865	−270.834	−229.817
AIC	796.347	874.696	735.730	709.669	661.635
CAIC	949.647	1,106.968	1,046.975	1,099.886	1,130.825
BIC	916.646	1,056.968	979.975	1,015.886	1,029.825

zero (Table 3 in the Appendix). Even though these findings are important, this study does not include this level of in-depth analysis. The inclusion or exclusion of non-significant indicators only changes the PLS-PM estimates very slightly and, thus, does not affect our inner model analysis. To assess whether the multicollinearity level in the formative measurement models is a critical issue, we investigated each variable's variance inflation criterion (VIF) values. Of all the formative indicators, the maximum VIF value was 2.847. Thus, the VIF clearly lies below the threshold value of ten and multicollinearity does not pose a problem in this study.

Evaluation of the structural model: Table 2 provides an overview of the assessment of the aggregate PLS path coefficients in the inner model as well as the FIMIX-PLS and ex post analysis results in respect of two segments: the mixing proportions of each segment ρ_s, and each endogenous construct's R-square value. A multi-group analysis was applied to test whether the path coefficients differ significantly between the segments. Instead of employing bootstrapping (Keil et al. 2000) or permutation-based (Chin and Dibbern 2009) testing routines, this paper draws on Henseler's (2007) novel non-parametric procedure to test the differences in group-specific PLS path model estimates. The latter method has been specifically designed for multi-group PLS-PM analyses and, thus, exhibits certain advantages in comparison to other proposed approaches (Henseler et al. 2009).

According to the FIMIX-PLS analysis, the endogenous construct exhibits an increased overall R-square, which represents the (by segment size) weighted sum of the segment-specific R-square values. The FIMIX-PLS overall R-square value of 0.761 is 28% higher than that of the global model results (path model estimation on the aggregate data level). In the first FIMIX-PLS segment, almost all inner model relationships are significant ($p<0.01$). In contrast to the global model results, the segment-specific results provide evidence of the various performance features' substantial and varying influence on overall customer satisfaction. For example, in the first segment, price policy significantly influences overall satisfaction, which does not occur in the aggregate-level analysis, or in the second segment. In addition, the analysis results of the second FIMIX-PLS segment are very positive. Even though the number of significant inner model relationships is somewhat smaller than in the first segment, the results are still more substantial than in the aggregate-level analysis. With regard to this segment, the R-square value of 0.487 is satisfactory in absolute terms, but is slightly lower than that of other analyses. Owing to the PLS-PM algorithm's methodological aspects, some driver constructs (e.g., periodic customer visits in the first segment) have a significantly negative influence on the overall satisfaction. The standard PLS-PM algorithm aims at minimizing error variance in the endogenous construct. Consequently, other constructs' negative influence should compensate for some driver constructs' (e.g., machines and systems) highly positive explanatory power. As a result, only positive values should be considered when interpreting segment-specific PLS-PM results in the present set-up.

With regard to the first segment, the results indicate that satisfaction with machines and systems has the strongest effect on customer satisfaction. Similarly, several dimensions that relate to the company's accessibility/reaction time, flexibility, or credibility/reliability exert a significantly positive influence on the endogenous construct. Customers in this segment are mainly concerned with company-level performance features, or "hard" facts relating to the product and quotations. However, in the second segment, customers'

Table 2: Impact on overall customer satisfaction – PLS path coefficients and t-values

Satisfaction with the:	Global	FIMIX			Ex post analysis		
		s = 1	s = 2	|diff|	s = 1	s = 2	|diff|
Machines and Systems	0.520***	0.793***	0.229**	.564***	0.780***	0.169	0.611***
	(7.232)	(18.478)	(1.960)		(13.695)	(1.507)	
Services	0.084	−0.166***	0.016	.182***	−0.142**	0.124	0.266***
	(0.215)	(3.054)	(0.161)		(2.199)	(1.069)	
Representation	0.018	0.037	−0.013	.050***	0.022	−0.045	0.067***
	(0.282)	(1.412)	(0.182)		(0.444)	(0.456)	
Quotations	0.104**	0.235***	−0.023	.258***	0.189***	0.045	0.145***
	(2.125)	(6.621)	(0.428)		(4.434)	(0.565)	
Company’s Flexibility	−0.063	0.114***	−0.126*	.240***	0.141***	−0.131*	0.271***
	(1.256)	(3.400)	(1.891)		(2.609)	(1.693)	
Employees	0.011	−0.066*	0.317***	.383***	−0.056	0.271***	0.327***
	(0.416)	(1.797)	(2.620)		(1.117)	(2.580)	
Execution of Instructional Training	0.054	−0.032	0.025	.062	−0.066	0.111	0.177***
	(0.907)	(0.663)	(0.427)		(1.353)	(1.400)	
Corporate Behavior	0.018	−0.071**	0.169*	.239***	−0.069	0.198**	0.267***
	(0.481)	(2.240)	(1.839)		(1.439)	(2.224)	
Company’s Accessibility and Reaction Time	0.098	0.178***	0.042	.137*	0.163***	0.015	0.149
	(1.332)	(3.993)	(0.554)		(2.604)	(0.129)	
New Product Development	−0.036	−0.185***	0.018	.203***	−0.173***	−0.160	0.014
	(0.493)	(4.595)	(0.299)		(3.630)	(1.398)	
Periodic Customer Visits	0.069	−0.119***	0.295***	.414***	−0.071	0.183**	0.254***
	(1.074)	(3.489)	(3.151)		(1.587)	(2.178)	
Price Policy	0.101	0.160***	0.069	.091*	0.119***	0.174*	0.055
	(1.546)	(4.624)	(0.984)		(3.018)	(1.699)	
Company’s Credibility and Reliability	0.003	0.265***	−0.194*	.458***	0.259***	−0.149*	0.408***
	(0.093)	(6.217)	(1.905)		(5.852)	(1.657)	
Offer of Instructional Training	−0.031	−0.019	−0.082	.057***	−0.044	−0.008	0.037***
	(0.339)	(1.334)	(1.155)		(1.030)	(0.090)	

Table 2: (continued)

Satisfaction with the:	**Global**	**FIMIX**			**Ex post analysis**		
		s=1	**s=2**	**|diff|**	**s=1**	**s=2**	**|diff|**
Product's Compatibility with Machines of Different Makes	−0.006	0.002	−0.029	.030***	0.031	−0.022	0.053***
	(0.162)	(0.090)	(0.530)		(0.0870)	(0.301)	
ρ_s	1.000	0.604	0.396		0.559	0.441	
R-square (Customer Satisfaction)	0.593	0.940	0.487		0.893	0.504	

*** significant at $p<0.01$ ** significant at $p<0.05$ * significant at $p<0.10$

T-values are shown in brackets and were obtained by means of the bootstrap routine (construct-level sign change option) with 500 subsamples and a number of cases equal to the number of observations in each segment.

overall satisfaction is strongly affected by "soft" factors that relate to interpersonal communication. Compared to other models, both satisfaction with employees and periodic customer visits have a significantly positive influence on the dependent variable. Moreover, satisfaction with the machines and systems is positively related to the endogenous construct, but to a far lesser extent than in the first segment. Overall, the drivers of customer satisfaction differ substantially across the two segments. In addition, multi-group PLS-PM analyses (Table 2) clearly indicate that most of these differences are significant ($p < 0.01$), thus showing that the segments are differentiable.

The next step involves the identification of explanatory variables that best characterize the two uncovered segments (Step 3 in Fig. 1). We consequently applied the CHAID algorithm (Biggs et al. 1991) by using SPSS Answer Tree 3.1 on observable variables, such as country of origin, company size, or other variables representing company characteristics. This method allows researchers to assess whether splitting the sample according to these variables' modalities leads to a significant discrimination between segment affiliation's dependent measures. The analysis showed that the variable "Is your plant part of a multinational corporation?" has a high potential for a meaningful a priori segmentation ($F_{1,279} = 297.220$; $p < 0.001$). This result is also supported by the χ^2-test results, indicating that there is a significant relationship between the explanatory and segment affiliation variables ($\chi^2_1 = 144.943$, $p < 0.001$). In accordance with these outcomes, segment one comprises plants belonging to multinational corporations, whereas the second segment consists of independent, smaller scale plants.

The resulting segment sizes are almost equal to the previous FIMIX-PLS analysis (Table 2) and cross tabulation shows that the classification corresponds 86.2% with the FIMIX-PLS classification. An evaluation of the PLS-PM estimates (Chin 1998; Henseler et al. 2009) of these two a priori segmented datasets confirms the satisfactory results (Table 2). The R-square value of the first segment is considerably higher than that in the global model, indicating an improved model fit. Even though the second segment's goodness of fit has increased in comparison with the previous FIMIX-PLS analysis, R-square still falls slightly below the global model result. However, in comparison to Festge and Schwaiger's (2007) analysis, the segments derived from the FIMIX-PLS ex post analysis clearly exhibit an increased overall model fit.

Concerning the importance of the different performance features, the segment-specific path analyses show almost congruent results when compared to the initial FIMIX-PLS analysis. Once more, in the first segment, the customers' overall satisfaction is primarily driven by performance features at the company level such as satisfaction with machines and systems. Moreover, financial features, such as price policy and quotations, significantly influence customers' overall satisfaction. In the second segment, customers rely more strongly on performance features that relate to interpersonal relationships with the company's employees. In addition to and contrary to the initial FIMIX-PLS analysis, corporate behavior plays an important role in customer satisfaction. A multi-group comparison shows that almost all the path relationships differ significantly across the two segments ($p < 0.01$), thus supporting the general notion that segments should be differentiable.

Conclusions

By applying FIMIX-PLS to uncover unobserved heterogeneity in the inner model PLS path model estimates, we are able to extend Festge and Schwaiger's (2007) study. This research provides a more complete picture of how the antecedents and the drivers of customer satisfaction affect the industrial goods market. Moreover, this study makes a strong case for further differentiated, segment-specific customer satisfaction management analyses to arrive at a considerably better model fit. The identification of different consumers groups with distinct estimates in the inner path model highlights the importance of segmentation in PLS-PM to shape effective marketing strategies.

The segment-specific driver analysis clearly shows that, depending on the customer's background, the factors through which a company can generally influence a specific customer's satisfaction level differ vastly. This matches the complex buyer-seller relationships in industrial markets (e.g., Homburg and Rudolph 2001). Customers from multinational companies rely more strongly on company and product-related features, whereas customers from independent plants favor "soft" factors reflecting personal contact or corporate behavior. By uncovering and treating unobserved heterogeneity through segmentation, this study's results contrast sharply with Festge and Schwaiger's (2007) findings. According to these authors, only features related to machines, systems, and quotations offer a significant chance to increase the customer's overall satisfaction.

The FIMIX-PLS extension of Festge and Schwaiger's (2007) analysis leads to further differentiated findings that have important managerial implications. Many companies in the industrial goods sector are technically-minded. Consequently, they assume that the product itself is the key driver of satisfaction. However, our research shows that personal interaction and processes accompanying the core products and services have great potential to enhance customer satisfaction. Nevertheless, these effects do not hold for the entire customer base as Homburg and Rudolph (2001) maintained. We support the notion that multinational industrial companies are more strongly finance-driven, as exhibited by centralized purchasing departments in their organizational structure. On the other hand, customers in independent plants are more often relationship-oriented, sustaining close and long-lasting relationships with their providers. Moreover, unlike the original study, our results show that satisfaction with the price policy has a significant influence on both segments. Consequently, Festge and Schwaiger's (2007, p. 201) conclusion that "a price strategy is not promising for the goals of a high level of customer satisfaction and consequently a high level of customer loyalty, customer retention, or positive word-of-mouth recommendation" should be reconsidered in the light of this study's findings.

Depending on the target group, industrial companies should consider either the "hard" or the "soft" factors of customer satisfaction management. Consequently, our results confirm the necessity for "adaptive selling" (Spiro and Weitz 1990), meaning that different selling approaches are required for different selling situations. Therefore, target-oriented customer contentment is a necessary requirement to achieve a high level of customer satisfaction.

From a methodological viewpoint, this study's results illustrate the complementary analytic potentials of response-based segmentation with finite mixture models in PLS-PM. By accounting for unobserved heterogeneity, our FIMIX-PLS analysis arrived at a considerably better model fit, rectifying potential sources of misinterpretation resulting from an aggregate level data analysis. This study of a common marketing research problem answerers Esposito Vinzi et al.'s (2007) and Ringle et al.'s (2009a) call for the use of FIMIX-PLS in applications. Such analyses are important to evaluate the approach's capability to identify and treat unobserved heterogeneity in PLS-PM.

Limitations and Future Research

Despite these very encouraging results, this study has some limitations due to the drawbacks of the applied methodology. In FIMIX-PLS, heterogeneity is only supposed to be concentrated in the inner model parameter estimates. Even though measurement model heterogeneity may be well reflected in heterogeneous inner model parameter estimates, there is no obvious closing guarantee that the ex post analysis can successfully disclose these differences. To overcome this FIMIX-PLS limitation, Esposito Vinzi et al. (2008) suggested that the response-based procedure (REBUS-PLS) should be applied to detect unit segments in PLS-PM. By repeatedly forming new data groups and computing group-specific outer and inner PLS path model estimates in the iterations of the algorithm, the approach uncovers heterogeneity in both the structural and the measurement models. However, since REBUS-PLS' optimization criterion depends on a PLS-PM goodness-of-fit measure (GoF), the approach is restricted to reflective measurement models and is, thus, deemed inappropriate for the analysis at hand. Recently, new developments were introduced regarding uncovering unobserved heterogeneity in inner PLS path model relationships and formative measurement models, such as PLS genetic algorithm segmentation (PLS-GAS; Ringle et al. 2009b) and PLS prediction-oriented segmentation (PLS-POS; Becker et al. 2009). These methodologies are, however, in an early stage of research and are not yet available in software implementations.

Another concern is that this study does not establish measurement invariance across the segments, which is a prerequisite for any multi-group analysis in structural equation modeling (Williams et al 2003).[3] When comparing segment-specific parameter estimates, researchers must ensure that measurement parameters (factor loadings, measurement errors, etc.) are similar across groups and that the identical constructs are measured in all groups. Researchers can thus ascertain that they compare the same kind of occurrences when interpreting significant differences in FIMIX-PLS results. There is a vast body of literature on measurement invariance (for a review, cp. Vandenberg and Lance 2000). However, research has not yet provided an appropriate test for PLS-PM. Covariance-based structural equation modeling techniques, such as Steenkamp and Baumgartner's (1998) approach, may be used as a work-around. Nevertheless, for methodological reasons, these procedures are usually inadequate for the non-parametric PLS-PM approach (Gudergan et al. 2008). As Sarstedt and Ringle (2010) pointed out, an appropriate means of testing measurement model invariance in PLS-PM may build on bootstrapping or permutation-test-based multi-group analysis results (Chin and Dibbern 2009) to answer the following four questions raised by Steinmetz et al. (2009, p. 600): "Are the measurement parameters (factor loadings, measurement errors, etc.) the same across groups? Are there pronounced response biases in a particular group? Can one unambiguously interpret observed mean differences as latent mean differences? Is the same construct measured in all groups?" Future research should present an appropriate procedure and an adequate test for evaluating measurement model invariance in PLS-PM for both reflective and formative measurement model stet-ups. This future contribution will be of fundamental importance when conducting multi-group analyses in the last step of a systematic application of the FIMIX-PLS approach.

Despite these limitations, our study proves valuable in several respects. It demonstrates how the development and subsequent application of new modeling techniques can contribute to extracting additional knowledge from prior research. In marketing, the various customer satisfaction index models, such as the European customer satisfaction index (ECSI; e.g., Hackl and Westlund 2000), are key areas of PLS-PM use and, thus, offer the greatest potential for supplementary analyses. Furthermore, the results show that a PLS-PM analysis on the aggregate data level can be seriously misleading, thus resulting in flawed management decisions regarding, for example, customer targeting, product positioning, or the determination of the optimal marketing mix. Considering the key role that customer satisfaction plays in establishing, developing, and maintaining successful customer relationships in industrial markets, these findings are highly relevant from a managerial point of view. Segmenting consumer response along multiple dimensions should lead to a richer understanding of the marketing mix's impact and allow the formulation of effective marketing strategies.

Endnotes

1 "Note that this presentation slightly differs from Hahn et al.'s (2002) original presentation."

2 Even though recent research shows that single items lag significantly behind multi-item measures in terms of criterion validity (Sarstedt and Wilczynski 2009), a single item may still be used as a measure to assess a construct on an aggregate level, as all respondents can simultaneously consider all those parts of the construct that they consider important (Nagy 2002).

3 The authors would like to thank the anonymous reviewer for this helpful remark.

Appendix

Table 3: Evaluation results of the formative measurement models

Factor	Performance Features	s = 1	s = 2
Satisfaction with the machines and systems (factor 1)	1. Reliability of the machines and systems	0.379*** (6.114)	0.470*** (3.575)
	2. Life-time of the machines and systems	−0.045 (0.860)	0.235* (1.717)
	3. Machine's/system's first-line-maintenance capabilities	0.109** (2.506)	0.048 (0.484)
	4. Technological advancement of the machines and systems compared to "state-of-the-art"	0.181*** (4.113)	−0.091 (0.724)
	5. Capacity of the machines and systems	0.137*** (2.846)	−0.007 (0.045)
	6. Functionality/user friendliness operation of the machines and systems	0.140*** (2.780)	0.076 (0.575)
	7. Appearance (design) of the machines and systems	0.037 (0.929)	0.106 (0.831)
	8. Quality of the provided operating instructions	0.068* (1.686)	0.086 (0.792)
	9. Cleanliness of the machine's/system's filling process	0.073** (1.985)	0.160 (1.458)
	10. Weight accuracy of the machines and systems	0.017 (0.413)	0.130 (1.039)
Satisfaction with the services (factor 2)	11. Delivery time of machines and systems	0.183** (1.971)	0.054 (0.411)
	12. Reliability of given target dates	−0.026 (0.243)	0.017 (0.108)
	13. Reliability of given statements	0.395*** (3.796)	0.271** (2.010)
	14. Quality of installation and commissioning services	0.154 (1.446)	0.189 (1.345)
	15. Duration of installation and commissioning services	0.165 (1.519)	0.111 (0.727)
	16. Timely availability of the after-sales services	0.001 (0.004)	0.103 (0.829)
	17. Local availability of the after-sales services	−0.025 (0.300)	0.210** (2.420)
	18. Fast processing of complaints/problems	0.060 (0.593)	0.097 (0.588)
	19. Price of after-sales services	0.083 (1.185)	−0.130 (1.374)
	20. Availability/delivery time of spare parts	−0.009 (0.083)	0.043 (0.328)

Table 3: (continued)

Factor	Performance Features	s = 1	s = 2
Satisfaction with the representation (factor 3)	21. Corporate representation by means of sales literature	0.378* (1.848)	−0.002 (0.010)
	22. Corporate representation by means of print media (i.e., periodical, professional journals)	0.314* (1.673)	0.349 (1.336)
	23. Corporate representation by means of the internet (i.e., Web site)	0.136 (0.869)	0.114 (0.502)
	24. Corporate representation by means of events (i.e., trade shows, conferences/symposiums)	−0.118 (0.815)	−0.205 (0.905)
	25. Possibility to utilize services via e-business	−0.080 (0.462)	−0.060 (0.290)
	26. Broadness of the product line	0.399*** (2.617)	0.853*** (4.026)
Satisfaction with the quotations (factor 4)	27. Composition of quotations	0.694*** (5.071)	0.519 (1.394)
	28. Transparency of quotations	0.277* (1.923)	0.502 (1.443)
Satisfaction with the company's flexibility (factor 5)	29. Company's flexibility regarding project partners	0.431*** (2.794)	0.687 (1.190)
	30. Company's flexibility regarding project revisions	0.459*** (2.978)	0.341 (0.592)
Satisfaction with the employees (factor 6)	31. Expertise of personnel	0.617*** (5.693)	0.828*** (8.472)
	32. Language skills of personnel	−0.088 (0.875)	−0.044 (0.439)
	33. Friendly appearance of personnel	0.438*** (3.060)	−0.024 (0.178)
Satisfaction with the execution of instructional training (factor 7)	34. Fixed price for instructional training	0.018 (0.110)	0.407** (2.199)
	35. Language of instructional training	−0.053 (0.310)	−0.051 (0.295)
	36. Quality of instructional training	0.649*** (2.845)	0.468** (2.372)
	37. Up-to-date topics of instructional training	0.568 (2.774)	0.822*** (3.588)
Satisfaction with corporate behavior (factor 8)	38. Company's legal form (i.e., family-owned company)	0.516** (2.502)	0 214 (1.247)
	39. Worldwide company presence	0.553** (2.293)	0.776*** (5.842)
Satisfaction with the company's accessibility and reaction time (factor 9)	40. Availability of personnel	0.314** (2.283)	0.367*** (2.714)
	41. Short reaction time regarding inquiries	0.545*** (5.152)	0.535*** (3.974)

Table 3: (continued)

Factor	**Performance Features**	**s = 1**	**s = 2**
Satisfaction with new product development (factor 10)	42. Compliance with local laws of measurement and calibration	0.141 (0.812)	0.424*** (2.911)
	43. Customer involvement in product development	0.266** (2.097)	0.338** (2.205)
	44. Exact compliance with international standards	0.568*** (3.936)	0.412** (2.207)
Satisfaction with periodic customer visits (factor 11)	45. Periodic visits by representatives of the company's local representation	0.562*** (2.873)	0.478*** (4.760)
	46. Periodic visits by representatives of the company's head office	−0.161 (0.664)	−0.246** (2.225)
	47. Company's offer of additional services (i.e., regular audits of the plant)	0.359** (2.049)	0.664*** (4.951)
Satisfaction with the price policy (factor 12)	48. Fixed product price of the machines/systems	−0.186** (2.050)	−0.435*** (3.002)
	49. Cost/performance ratio of the machines/systems	0.812*** (14.973)	0.955*** (16.439)
Satisfaction with the company's credibility and reliability (factor 13)	50. Company's credit rating and reliability	0.816*** (13.694)	0.783*** (12.059)
Satisfaction with the offer of instructional training (factor 14)	51. Possibility of instructional training	0.826*** (15.068)	0.920*** (12.369)
Satisfaction with the product's compatibility with machines of different make (factor 15)	52. Product compatibility with machines of different make	0.754*** (17.967)	0.974*** (13.768)

*** significant at $p < 0.01$ ** significant at $p < 0.05$ * significant at $p < 0.10$

T-values are shown in brackets and have been obtained by means of the bootstrap routine (construct-level sign change option) with 500 subsamples and a number of cases equal to the number of observations in each segment

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